This paper estimates the empirical link between five structural service design choices and service profitability in the context of the U.S. domestic airline industry. The results of a fixed effects panel regression model provide evidence that the structural design choices of the (1) extent of market rivalry, (2) complexity of the aircraft fleet deployed, (3) operations scale, (4) network routing structure, and (5) capacity management strategy explain about two thirds of the differences in operational profitability among airlines. Two of the service design choices, market rivalry and fleet complexity, explain over 50% of the impact on airline operational profitability.

**KEYWORDS:** fixed effects regression, service profitability, structural design choices, service design, lean consumption
ability to manage capacity (matching capacity with demand and revenue management to sell perishable seats).

The objective of this study is to contribute to the body of service operations knowledge with an empirical industry study linking structural service delivery choices directly to service operations profitability. The contributions of this study are to: (1) provide empirical evidence of the significance of structural design choices on operational profitability for a major service industry; and (2) provide insight into the effectiveness of specific structural design choices in this industry, the domestic US airline industry. The empirical analysis underscores the potential for using "big data" and business analytics to better understand links between strategic design choices and business performance.

Two of the structural design choices for The U.S. airline industry, operations scale and capacity management have been studied extensively over several decades. This research confirms prior findings that capacity management and scale are positively linked to profitability. The design choices of market rivalry, fleet complexity, and flight network structure involve complex economic interactions that we detail in the literature section. Much less has been reported about the potential of these decisions to impact profitability. Somewhat unexpectedly, our fixed effects panel regression model estimates suggest that market rivalry and fleet complexity dominate the other decision variables in their impact on profitability.

In section 2 we summarize research theories and studies on the structural design of the service delivery network. This includes a review of the relevant literature specific to the service delivery choices in the domestic airline industry. In section 3 we propose a set of hypotheses and describe our experimental methodology including operational data, metrics, and model estimation procedures. Section 4 provides a discussion of the empirical findings relating to our hypotheses, and section 5 concludes with key contributions and limitations.

THEORY OF STRUCTURAL SERVICE SYSTEM DESIGN

In this section we review studies that examine the significance of structural choices in the service delivery system and current service design strategies and practices of the U.S. domestic airline industry.

Structural Service Design and Service Performance

The Service System Triad (Roth and Menor, 2003) consists of three constructs: service delivery system design choices, the target market that defines who the right customers are, and the service concept specifying the product bundle offered. The service delivery system design choices consist of structural choices, infrastructural choices, and integration choices. Structural choices identify key aspects of the physical delivery system including facilities, locations, layouts, technology, equipment, and network configurations for delivering service. The infrastructural design relates to people, leadership, and performance management. They define the necessary characteristics of employees and the organization's policies, practices, and processes. Integration choices define mechanisms for coordination, learning and adaptation, and the nature of service supply chains. This collection of strategic design choices defines the realized service delivery system (Roth & Menor, 2003).
Giloni et al. (2003) investigate service design choices in the selection of distribution channels to customers for property and casualty insurance. Traditionally, insurance products were distributed by agents; advances in technology choices enabled new forms of distribution that integrate web-based distribution supported by company call centers. Firms in the property casualty industry now face several service design issues including (1) how to determine the distribution channels and intermediaries, (2) how much of each type of intermediary to deploy in each channel, and (3) the service levels to provide the customer in each channel. The authors develop a framework for the design of distribution systems for property and casualty insurance and use empirical data to test for consistency. The model does not relate design choices to firm profitability.

A case study of the South Carolina Department of Motor Vehicles investigated service design principles and efficiency for a public service organization (Karwan & Markland, 2006). Based on an adaption of the Goldstein et al. (2002) government services planning model, the authors determine that strategic alignment, effective information technology deployment, and clear separation of front and back office tasks are vital for increasing public sector service efficiency. Outcomes from improvements made to the South Carolina Department of Motor Vehicles include a substantial decrease of customer wait times, a significant increase in transactions conducted on the web, improved process flows, and fewer complaints.

The structural service delivery design of the San Francisco Public Library was identified as contributing to service performance deficiencies (Apte & Mason, 2006). Library customers’ experiences acquiring books through interlibrary loans were diminished by the realization of long cycle times and delivery variability. The structural design of this service was a hub-and-spoke network configuration with the Main Library serving as the hub. The recommendations of Apte and Mason (2006) enabled the library to significantly lower both cycle times and costs, and increase system capacity by deploying a new network design consisting of a cross docking network with pre-sorting of materials and workload balancing of delivery routes.

Silvestro and Silvestro (2003) describe the service delivery system design for National Health Service Direct, a call center for patients in the United Kingdom. With data from the first three years of operations, the authors evaluate the strategic alignment of its service concept, operational objectives, and the design of its service delivery system. They identify a major deficiency in the process: the lack of an explicit service specification to serve as a basis for the design of each call center. In its absence, each call center assumed responsibility for the design of its services, and the organization’s national service delivery system became strategically misaligned.

Li et al. (2002) investigate the relationship between strategic design choices and performance for community hospitals. Model inputs include the structural choices of location, bed size (capacity), specification of equipment and process technology, and the outpatient service network. Infrastructural inputs specify details of demand management, workforce management, and continuous improvement programs. The model demonstrates causal relationships between structural and infrastructural choices on quality, cost, and financial performance outcomes for 151 community hospitals.
Structural Service Delivery Choices for the US Airline Industry

Tsikriktsis (2007) empirically links service operational performance and profitability in the US airline industry. The author creates a model that explicitly links capacity utilization, quality (delivery reliability), and focus to profitability. This is a longitudinal study of operational performance for two segments of the US airline industry: focused airlines with regional or national service and full service airlines with international routes. Two main conclusions of this study are that operational performance and profitability are contingent on the operating model, and that capacity utilization is a stronger driver of profitability for full-service airlines than for focused airlines. Our study differs from Tsikriktsis’ (2007) in several significant ways. First, we focus directly on the effects of service structural design choices (i.e. market rivalry, flight network centrality, fleet complexity) on profitability, while Tsikriktsis’ study links performance metrics (i.e. load factors) to profitability. We make no attempt to segment the industry, instead choosing to evaluate metrics of service network design for each airline. Tsikriktsis’ (2007) full service airlines included international flights, which have higher margins and economies of scale from long flight lengths. We exclude international flights, as they involve different service delivery processes, including longer setup times and longer flights. We also find that many of the airlines we would conceptualize as focused airlines today violate the characteristics of fast turnaround time and the avoidance of congested hub and spoke airports. For example, the former America West operated from a hub in Phoenix and had turnaround times that are on average 30 minutes longer than Southwest. Air Tran and Jet Blue, neither of which are subjects of the Tsikriktsis (2007) study, operate from hubs at Atlanta and JFK, New York, both congested airports.

Our identification of structural design choices in the domestic US airline industry is accomplished through an extensive literature search detailed in sections 2.2.1 through 2.2.5. Our discussion of structural service choices will proceed as follows: (1) the choice of city-pairs to serve, which determines market potential and the degree of market rivalry (number of competitors); (2) the determination of a flight routing network to serve the city pairs; (3) the selection of an aircraft fleet to deploy in the flight routing network; (4) the scale of operations which is influenced by both the density of activity on the current flight network and expansion of the network over time to serve new city-pairs; and (5) capacity management, which is the quantity of seat miles deployed to satisfy expected demand in the flight network. We will describe controls for differences in “factors of production,” in the experimental design section. The reader is referred to Banker and Johnston (1993) for a comprehensive review of cost drivers and performance factors for the domestic US airline industry.

Market Choices and Competitive Rivalry

The choice of markets to serve in this industry involves the selection of city-pairs to provide transportation services, and the acquisition of airport gates (U.S. GAO, 2014). This decision predetermines a level of competitive rivalry which impacts pricing power, revenue per seat mile, and operating margins.

The forces of rivalry among existing competitors are addressed most recently by Michael Porter (2008). Porter concludes that price is the most likely form of competition when services offered by competing firms are nearly identical and when customer switching costs are low. Price competition is also fostered in economic environments where fixed costs are high and marginal costs are low. This environment entices firms to cut prices below average costs to a level approaching marginal costs. For the airline industry, the marginal cost of an additional
passenger occupying what would have been an empty seat is extremely low. It consists of the additional fuel consumed and any food and drink amenities that are provided without charge. Price competition is also prevalent when services are perishable. An empty airline seat is certainly a perishable service; it provides no value to the firm after an aircraft departs. The domestic airline industry is a prime example of price based competitive rivalry. Customer switching costs are low and price discounting is obvious to both customers and competitors. Fare discounts are quickly matched by competitors. A common advice in the travel industry is to book airline fares on Tuesday or Wednesday during the time period when airlines adjust fares and discounts are matched. Sophisticated search engines facilitate the process of identifying low price fares. Porter (2008) concludes that price competition as practiced by the domestic airline industry is the most destructive basis for competition; it transfers profits directly from the industry to customers. This research will estimate the magnitude of the wealth transferred by price competition.

Customer behavior is not the only factor that affects profitability. Because of the structure of the airline industry, airlines often share resources within their networks. These resource sharing opportunities allow airlines to gain economies of scope, which often leads to multiple city-pairs served by the same rivals (multimarket). This significantly affects the competitive dynamic. It has been shown that airlines overlapping in multiple markets are less aggressive toward each other than those that meet in one or only a few markets (Baum and Korn, 1996). When a hub is price-attacked by a rival, price retaliation in the attacker’s hub is a common response (Nomani, 1990). Further, Gimeno and Woo (1999) found that profitability increased if the firm participated in markets with strong resource-sharing opportunities. Multimarket contact reduced intensity of rivalry and increased profitability. However, intensity of rivalry increased and profit decreased if a focal firm (i.e., a firm in a specific market) was absent from markets where focal-market rivals obtained strong economies of scope. The lack of mutual forbearance in such situations allows more efficient rivals to compete more aggressively, thus increasing the intensity of rivalry and decreasing profitability. The results of Xu (2011) included a finding that as the intensity of rivalry increases its organizational performance decreases. Such studies suggest that an increase in the number of airlines that do not compete directly in the same markets and do not engage in significant resource-sharing will increase the intensity of rivalry and reduce profitability. The reader is referred to Chang and Yeh (2001) for a general framework of airline competitiveness.

Configuring a Flight Network

The choice of the structural design components of the service delivery system in the airline industry includes configuring a network of origins and destinations referred to as a flight schedule or network, a major determinant of an airline’s cost structure (Barnhart and Cohn, 2004). Flight networks can differ significantly in the “degree of directness” of the network paths. Aircraft route structures are typically designed around the hub-and-spoke concept where an airline’s flights originate or arrive at a central location to allow for the consolidation and redirection of passengers (Ryerson & Kim, 2013). Rosenberger et al. (2002) define this strategy for an airline as a flight network with a large percentage of the flight segments into or out of a small subset of stations called hubs. The degree of hub use in a network is a key metric that characterizes an airline’s service delivery network. Chen (2007) states: “Hub-and-spoke networks consolidate traffic flows from different origins and ship them via hubs to different destinations so as to reduce overall transportation costs.”
Bania et al (1998) identified several types of structures, including mono-hubs, dual hubs and diffused systems. A mono-hub has the lowest degree of directness, with all passengers originating at non-hub locations routed first to the hub where passenger loads are aggregated and re-routed to outbound destinations. The only passengers receiving direct service in the mono-hub design strategy are those whose travel originated at the hub location or those with the hub as a destination. The graph representation of this is a single vertex (the hub) with N-1 connections to each of the non-hub vertices. In this research we refer to a mono-hub as a centralized flight network. The advantages and disadvantages of centralized/decentralized flight networks are summarized in Table 1. The degree of centralization/decentralization in a supply chain context has recently been studied by Schmitt et al. (2015). The centralized network provides economic advantages by aggregating passenger demand at the hub location and thereby enabling higher flight frequency and larger aircraft load factors (proportion of aircraft seats with revenue paying passengers). (Fu et al., 2010; Ball, 2007; Saunders & Shepherd, 1993; Gillen & Adib Kanafani, 2005; Adler, 2001; Bruekner & Zhang, 2001; Nero, 1999; Dobson & Lederer, 1993). Ball (2007) reports the centralized hub network appears to have economic advantages primarily on relatively longer flight segments. The hub network strategy creates the operational wastes of longer passenger throughput times (diminishing the lean consumption value) and the physical waste of multiple flight segments with miles flown exceeding distance between origin and destination. It is also recognized that hub airports have become increasingly congested with waves of arriving flights followed by waves of outbound flights scheduled at convenient travel times for passengers (Button, 2002; Ritveld & Brons, 2001). This creates airport demand variability, which lowers airline productivity by increasing the degree of variation and undermining delivery reliability. To be effective, the benefits realized from centralized hub networks must exceed the costs of transporting passengers increased distances and the necessity of using multiple service encounters.

Table 1: Advantages and disadvantages of flight network centralization

<table>
<thead>
<tr>
<th>Centralized flight network</th>
<th>Decentralized flight network</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Benefits</strong></td>
<td><strong>Benefits</strong></td>
</tr>
<tr>
<td>Aggregate passengers</td>
<td>Shorter throughput times for customers</td>
</tr>
<tr>
<td>Reduce transportation costs</td>
<td>Increase in customer value</td>
</tr>
<tr>
<td>Higher load factors</td>
<td>Fewer miles travelled by customers</td>
</tr>
<tr>
<td>Higher flight frequencies</td>
<td>Fewer delays, disruptions</td>
</tr>
<tr>
<td><strong>Disadvantages</strong></td>
<td><strong>Disadvantages</strong></td>
</tr>
<tr>
<td>Longer throughput times for customers</td>
<td>Some routes not economical</td>
</tr>
<tr>
<td>Customers travel more miles</td>
<td>Lower capacity, higher cost aircraft</td>
</tr>
<tr>
<td>Requires seats on multiple flight segments</td>
<td>Reduced flight frequency</td>
</tr>
<tr>
<td>Operations at congested hub airports</td>
<td>Flight delays and disruptions of flight network</td>
</tr>
<tr>
<td>Flight delays and disruptions of flight network</td>
<td>Increases in lost luggage</td>
</tr>
</tbody>
</table>

By contrast, a decentralized flight network would route flights more directly from origin to destination, resulting in a high “degree of directness” and fewer average flight segments (Bania et al., 1998). Airlines using this form of structure are often referred to as point-to-point or focused carriers (Ball, 2007; Tiskriktsis, 2007). In the extreme case of all direct flights, this is a
fully connected graph with all N vertices having N-1 edges. Point-to-point flights have the advantages of the shortest distances traveled (miles flown equivalent to distance between origin and destination), with fast passenger throughput times and high delivery reliability (quality). There is no need to wait for the transfer of baggage and for passengers from delayed connecting flights. Aircraft utilization (proportion of day spent flying) is typically increased (Flouris & Walker, 2005). This service delivery network strategy has the highest customer value and minimizes waste in the customer's consumption process (Womack & Jones 2005). Tsikriktsis (2007) found focused airlines (e.g., Southwest Airlines), characterized by a high degree of directness, showed profitability more than double that of full-service carriers (i.e., those using a centralized hub design and a more complex aircraft fleet). Avoiding congested hub airports and using a simpler route structure allowed such airlines to have greater delivery reliability and profitability. The disadvantage of the point-to-point network is that some edges may not have sufficient demand to generate economical service.

There is also a value and revenue effect on profitability generated by the design of the service delivery network. Sasser et al. (1978) first defined this as the “service concept,” which includes choices of service delivery methods and the customer’s direct experience of both the service and the value of the service. The service delivery design decision directly influences value from the customers’ perspective in the following way. Airline service delivery systems with a high degree of directness will, on average, provide shorter, more direct paths, while networks with low directness resulting from a hub design will have longer, slower paths. Service networks with a strong hub design create more indirect routing for passengers, thereby increasing the wastes of waiting and longer flight times (Womack and Jones, 2005). While airline passengers are generally segmented into time-sensitive business passengers and cost-sensitive leisure travelers, we argue that both segments value shorter and more direct routing.

The economics of the flight network centrality decision are obviously a complex set of interacting factors that determine the overall profitability outcome. The experimental results provide insight on the basic issue: is more or less flight centralization required to improve airline profitability?

Choosing an Aircraft Fleet

Today there are two potential suppliers for larger scale aircraft (Boeing and Airbus) and several manufacturers of smaller regional jets. The fleet selection decision mirrors production technology decisions (Banker and Johnston 1993). Aircraft model choices exist that differ in capacity, operating costs, and setup times. The choice of aircraft types is often modeled as an assignment optimization problem that accounts for the many factors and constraints created by the route structure (Barnhart et al., 2009; Gao et al., 2009; Ahmed & Poojari, 2008). A study by Daraban (2012) found that airlines flying a predominantly point-to-point route structure maintain more homogeneous fleets than full-service carriers. This is often cited as a contributor to low unit costs associated with point-to-point carriers.

The structural choices for fleet complexity range from standardizing on a single “best compromise” aircraft from one supplier (low fleet complexity) to deploying as many as eight different aircraft from as many as three different suppliers (high fleet complexity). The advantage of a more complex fleet for the service organization is the ability to more closely match aircraft operating characteristics to the demand patterns of specific flight segments (Lohatepanont & Barnhart, 2004).
The costs of choosing a more complex aircraft fleet include the need to train pilots, crew, and mechanics on multiple platforms, scheduling constraints, and the management of more complex maintenance and repair programs (Flouris & Walker, 2005).

**Determining Operations Scale**

The scale of flight operations is the choice of the number and size of markets served, the frequency of service for each city-pair, and the choice of aircraft utilized. A larger operational scale supports the deployment of larger aircraft with more seats, decreasing the cost per seat mile. It also allows the amortization of fixed costs (management, scheduling, operations control, advertising, maintenance, overhead, etc.) over a larger economic base. According to Nero (1999), increases in financial return are not constant as network size increases. However, increasing network size still provides competitive advantage. According to Rubin and Joy (2005), hub domination is also a form of economy of scale. An airline that dominates a hub airport has the ability to engage in predatory pricing to ward off market entrants. Larger full-service carriers often control long-term gate leases, making it difficult for others to gain access to the airport (Rubin & Joy 2005, U. S. GAO 2014). Hub domination is not a true form of scale, but instead is a strategy for repelling competitors through price cutting, which can erode profits.

Airlines often seek to increase their market share in order to increase profitability. In the late 1990’s many low-cost airlines (i.e., point-to-point carriers) attempted to expand more aggressively into larger airports. Ultimately, many of them went bankrupt due to the hub domination effect described earlier (Daraban, 2012). Ball (2007) argues that the short-haul market favors the point-to-point network structure. Further supporting this argument is the fact that the market share of low-cost carriers increased from 16% in 1993 to 36% by 2010 (Daraban, 2012). The reader is referred to Johnston and Ozment (2013) for a review of 30 years of research on returns to scale in the US domestic airline industry. While earlier research found no evidence of returns to scale, they conclude the industry has experienced positive returns to scale during the last 20 years.

**Controlling Capacity**

There are two major strategic choices for controlling capacity in the airline industry. The first relates to decisions for adding capacity to meet industry growth and the second is revenue management processes to fill unused seats in a competitive marketplace. There are strong links in the airline research literature between revenue management, capacity management, load factor, performance, and profitability. In general decision processes that optimize seat capacity with market demand across the flight network and effective revenue management processes increase load factors and increase profitability.

Jenatanabi (2013) states that the passenger load factor is one of the most important factors to evaluate the performance of an airline and defines it as the ratio of revenue passenger-miles to available seat-miles or:

$$\text{Load Factor} = \frac{\sum (\text{Number of Passengers Carried} \times \text{Distance})}{\sum (\text{Number of Available Seats} \times \text{Distance})}$$ (1)
Recent domestic U.S. airline load factors have averaged about 84% (IATA Press Release 2014). Load factors have been rising since deregulation of the airline industry; by comparison, the domestic load factor averaged about 60% in the 1980s (Saunders and Shepherd, 1993).

Load factor as a measure of airline performance has been studied for decades. Early researchers observed that, since deregulation in 1978, profitable airlines have higher load factors (Van Scyoc, 1989; Antoniou, 1992; Schefczyk, 1993). Van Scyoc (1989) reported that, prior to deregulation, airlines competed on service rather than cost, resulting in lower load factors on average during the regulated era than during the de-regulated era. Using mainly 1980’s airline data, it was observed by Saunders and Shepherd (1993) that load factors were higher for airlines with larger, more centrally located hubs. Hubs became a characteristic of airline structure after de-regulation to obtain economy of scale. Schefczyk (1993) found that high load factors, high efficiency, and high revenue predict high airline profitability.

Inzerilli and Jara-Diaz (1994) studied the link between load and capacity management strategy. In the process, the authors acknowledge that if one were to consider only a single operational measure of airline performance, it would probably be the load factor. In a study of group revenue management, Yuen (2003) asserts that any airline that has excess capacity has the opportunity to do better (by increasing its load factor). Dai et al. (2005) maintain that, after 9/11, there was a change in emphasis in airline strategy from revenue maximization to load maximization. Further, load factor has emerged as the key measure of capacity utilization in the airline industry (Rajasekar and Fouts, 2009; Collins et. al., 2011). According to Heufner and Largey (2013) capacity considerations are an integral part of revenue management.

DATA DESCRIPTION AND EXPERIMENTAL METHODOLOGY

The US Airline industry is selected as the subject of analysis for this case because a substantial amount of data on structural service design is available. This section describes the conceptual model tested in this case study, a definition of the data sample used, the metrics employed, and the process of model estimation.

Conceptual Model

The conceptual model depicted in Figure 1 defines the structural service design choices described in the prior section as determinants of service profitability. The specific structural service design choices we investigate in this research are: (1) the structure of the service delivery network (i.e. the flight routing network); (2) the complexity of the aircraft fleet deployed; (3) the scale of the service delivery operations; (4) the extent of market rivalry between competitors; and (5) the ability to manage aircraft fleet capacity.
Service Delivery Structural Design Hypotheses

The empirical model is designed to estimate the significance of the service delivery structural choices on operations profitability and to test the following hypotheses formulated from the research literature.

**Hypothesis 1.** Differences in structural choice of the service delivery network routing structure (V2) will impact service profitability (V1). (The direction of this effect is not established in the literature.)

**Hypothesis 2.** Differences in the structural choice of fleet complexity (V3) will impact service profitability (V1). (The direction of this effect is not established in the literature.)

**Hypothesis 3.** Differences in the structural choice of operational scale (V4) will be positively correlated with service profitability (V1). (Johnston & Ozment. 2013; Xu 2014)
Hypothesis 4. Differences in the structural choice of market rivalry (V5) will be negatively associated with service profitability (V1). (Porter, 2008)

Hypothesis 5. Differences in the structural choice of capacity management will be positively correlated with service profitability (Schefczyk, 1993)

Adjustments to reduce model bias

The empirical control model defined in Subsection 3.4 is a fixed effect regression model utilizing dummy variables to control for omitted variable bias. In instances where we have knowledge of variation that will bias the model estimation, adjustments are made to the data prior to estimation. This reduces the range of variability that dummy variables must estimate providing more reliable estimates of the strategic choice variables.

Cost drivers controlled in the research include the differences in (1) fuel costs between airlines; (2) legacy labor contracts creating differences in salary for pilots, flight crew, maintenance personnel, and management salaries; (3) expenditures for food and beverages served onboard; and (4) advertising and promotional activities. Potential bias from differences in these cost drivers were removed by the following data adjustments.

Jet fuel is a major cost driver for the airline industry ranging from 20-30% of total operating costs. During the period of this study, fuel costs approximately doubled from slightly more than $1 per gallon to over $2 per gallon. More importantly, there is a significant disparity in fuel costs/gallon between airlines. In 2007, jet fuel cost varied from $1.87 for Southwest Airlines to $2.68 for Delta Airlines. This cost disparity is attributed to fuel hedging strategies with differing proportion of spot market purchases and futures contracts. To correct for the influence of fuel hedging activities on service profitability, we calculate the average jet fuel cost for all nine airlines quarterly and restate airlines’ fuel costs based on the quarterly average cost per gallon. In the adjusted data, all airlines pay the same quarterly price for jet fuel.

There are notable salary differences between airlines during the time period of this study. Typically, the newer “low cost” airlines have lower salaries for management, pilots, and maintenance, while the older “legacy carriers” have significantly higher salary structures. For example, in 2004 the average quarterly pilot salary of AirTran Airlines was $32,000, while the Northwest Airlines pilot salary was $60,800. To adjust for the influence of salary structures on service profitability, we determine and average quarterly salary for all airlines for management employees, pilots, and maintenance personnel. The airlines’ employee costs are then restated based on standardized average salaries.

Differences between food and beverage costs per passenger reflect two different strategic choices. First, airlines that choose to focus their service delivery network on longer flight segments incur higher costs for food and beverage service. Secondly, an airline may attempt to differentiate its service offering by increasing expenditures on food and beverages. To adjust for this cost category, a regression model of food/beverage cost per airline per quarter is regressed on the average flight length by airline by quarter. The resulting regression has an $R^2$ of 0.87 with a slope of 0.0063 dollars per passenger per mile flown. Airline food/beverage costs are restated as a function of average flight length.
Advertising costs were included as a component of operating costs in the financial database. These costs are reversed and operating profitability restated to exclude advertising and promotion costs.

The data adjustments ensure that all airlines pay the same price for key factors of production: jet fuel, personnel salaries, food and beverage, and advertising. Collectively these factors of production represent 60% to 70% of an airline's operating cost structure.

The airline industry is a brutally competitive industry with price and convenience being the major considerations in consumer purchasing decisions (Porter, 2008). Bankruptcy reorganization has been common in this industry. Opportunities to expand into new markets are facilitated by mergers and acquisitions resulting from bankruptcies (Gong & Firth, 2006). Through acquisitions, airlines can increase their market power or coverage, enhance operating efficiencies, or overcome regulatory entry barriers (Sherer & Ross, 1990). For example, between 1989 and 1993 six major US carriers filed for chapter 11, with three ceasing operations. The remaining airlines significantly improved their aggregate operational and financial performance (Jayanti & Jayanti, 2011). Therefore, reorganization due to bankruptcy may improve the competitive position of an airline and have a positive impact thereafter on service profitability. Several airlines in our study filed for reorganization under Chapter 11. None of these companies were liquidated, but emerged from bankruptcy after reorganization. Bankruptcy events are a potential source of bias in the model estimates. Since we know who filed bankruptcy and when they filed, this event information is included in the model as a binary variable.

Data Sample

This study uses quarterly operational data of all domestic flights for nine major US carriers in the period 2004-2007, a total of 12.35 million flights. The timeframe of 2004-2007 for the study was chosen for two important reasons. This timeframe had a reasonably uniform and stable economic environment minimizing the impact of external economic variation on operational profitability. The banking crises started in 2008, producing a severe recession and economic pressures on the domestic airline industry. More importantly there were several mergers in the airline industry after 2007, which reduced the number of potential participants and the amount of data available for analysis. These include United Airlines merging with Continental, Delta with Northwest Airlines, Southwest with AirTran, and US Airways with American. Extending the analysis beyond 2007 reduces the unit of analysis from 9 airlines to 5 airlines, significantly limiting the data available for efficient model estimation. Including data periods prior to 2004 would introduce a significant source of variability during the post 9/11/2001 period including quarters where the airlines were not flying or had reduced flight schedules. This is also a period when airlines were receiving federal subsidies to continue operations.

The operational data is available from The Office of Airline Information of the Bureau of Transportation Statistics. Other empirical studies that use this data source include (Tsikriktsis & Heineke, 2004; Tsikriktsis, 2007; Deshpande, 2012; U. S. GAO, 2014; Johnston & Ozment, 2013). This data is partitioned into domestic and international operations for both operational and financial performance. It includes a table of scheduled and actual departure and arrival times reported by certified US air carriers that account for at least one percent of domestic scheduled passenger revenues (www.transtats.bts.gov) and provides such additional information as origin and destination airports, flight numbers, scheduled and actual departure
and arrival times, cancelled or diverted flights, air time, and non-stop distance. The nine major
US carriers investigated in this study are American, Jet Blue, Continental, Delta, AirTran,
Northwest, United, US Airways, and Southwest. Commuter airlines, international flight segments
of domestic carriers, and charter operations were excluded from this analysis. The operational
data was paired with quarterly financial performance data from the same source as the
operational data. The financial data allows the isolation of measures of profitability, including
operating income for domestic operations and assets employed in domestic operations.

Venkatraman and Ramanujam (1986) validated the use of financial and operational secondary
source data for single industry studies. This technique has been used previously by (Tsikriktsis
& Heineke, 2004; Tsikriktsis, 2007). We therefore posit the data is appropriate for this research.
We also note that the use of single industry airline data has the advantage of uniformity, as
there is little difference in the competitive environment of the domestic airline industry. None of
the major airlines have been able to differentiate their offerings with value added services; they
all essentially compete on price. In an environment of pure price competition, differences in
service profitability are largely caused by differences in service structural design.

The Definition of Metrics for Service Structural Design Choices

This section provides a detailed description of the construction of metrics for each of the seven
structural variables of the conceptual model (Figure 1). All metrics are calculated quarterly for
each airline for each of the 16 quarters in the study.

The profitability of the service system (V1) is measured by a return on assets metric, specifically
the quarterly operating income earned from domestic operations divided by the assets
employed in domestic flight operations. Operating income has the advantage that it excludes
financial structure decisions and is a pure measure of the financial contribution from structural
service design decisions. Adjustments to the stated domestic operating income are made for
differences in fuel costs, food costs, salary structure, and advertising and promotion costs as
described in subsection 3.1.2.

The hub index (Bania et al., 1998) is a key airline industry metric defining the service delivery
network routing structure. The hub index characterizes the degree of centrality in the network
structure (V2) that routes passengers from origin to destination. We measure the hub index by
the percentage of an airline’s flights that originate from its four most frequently used airports
(four airport frequency). This metric is evaluated quarterly by airline for each of the 16 quarters
of the study. Airlines that design a flight network with one or more hubs will have a high hub
index as shown in the histogram of Figure 2 for Northwest Airlines. By contrast, the Southwest
Airlines network of direct flights has a relatively low hub index. This hub index was used by
Bania et al. (1998) and is an extension of the two-group categorical variable (full service and
focused) used by Tiskriktsis (2007). While there are a number of other metrics for network
structure, we argue the four airport frequency is adequate since the airlines investigated have
four or fewer hub locations. Sensitivity analysis for other measures of hub use, such as the Gini
index, did not materially change the conclusions of this research.
The structural service choice for the aircraft fleet to be deployed (V3) can vary significantly. Southwest Airlines’ structural choice is an example of low complexity. Until the recent merger with AirTran, their fleet consisted of one aircraft model from one supplier, the Boeing 737. The other extreme in complexity is US Air with eight different aircraft models: Boeing 737, Boeing 757, Boeing 767, Embraer 170, Airbus 320, Airbus 330, Airbus 319, and Airbus 321. The metric for fleet complexity (V3) is compiled by counting the number of distinct aircraft models for each airline for each quarter of the study. Different configurations of the same model; the Boeing 737-200, 737-300 and Boeing 737-400 would be counted as one in the complexity metric.

The operations scale metric (V4) is defined as the total seat miles flown on all domestic flight segments during the quarter. It is the sum of the product of the number of aircraft seats times the distance flown for each flight segment.
The average number of competitors is a primary metric for market rivalry (V5) (U. S. GAO 2014). This metric is calculated as a weighted average of the number of competitors on each flight segment flown for each airline. The number of competitors on a flight segment varies from zero to as many as five. The weights are the ratio of the number of flight segments flown on an individual segment for each quarter to the total flight segments flown by the airline for that quarter.

The industry metric load factor is used to gauge the effectiveness of capacity management and revenue management (V6) by the airline. Load factor is measured as the number of revenue passenger miles expressed as a percentage of the available seat miles flown. It measures the proportion of an airline’s output that is actually consumed.

Bankruptcy (V7) is modeled as an indicator variable with zero representing the absence of a bankruptcy proceeding and 1 representing the condition where the organization is currently in bankruptcy proceedings. Bankruptcy entry and exit dates are readily available in public databases.

Each of the six metrics for the model variables were tested for significant deviations from a normal distribution. In two instances, network routing structure and load factors, improved distributions could be obtained with variable transformations.

Model Selection and Estimation

The unit of analysis for this research is a major US airline’s domestic operations. The data for each of the nine airlines consists of cross-sectional explanatory variables measured over 16 time periods. This data structure is commonly referred to as panel or time series cross-sectional data. The data consists of nine cross-sections (one for each airline) and twelve time series observations (three years of quarterly observations). The dependent variable is defined as operating profit for domestic operations divided by the assets invested in domestic operations for each of the service providers. The primary explanatory variables are quarterly calculations of metrics for each airline’s structural design choices. These estimate the network routing structure, the fleet complexity, the operations scale, the extent of market rivalry, and capacity management.

There are two major obstacles to assessing causality in panel data. The first is the observational nature of the data. It lacks the control data and random assignment that experimental designs require. As a result, variables that cannot be observed or cannot be measured could significantly impact the resulting statistical inferences. The second obstacle is that ordinary least squares (OLS) estimates of panel data usually violate the normality assumptions of the model errors. These deviations include contemporaneous disturbances in the errors, heteroscedasticity of the errors across the cross-sectional units of analysis, and autoregressive errors. To minimize the impact of these problems, the empirical model utilized in this research has fixed effect terms (Allison 2009) and utilizes Parks (1967) method for parameter estimation.

In some instances, a fixed effect regression model (Allison, 2009) can control for variables in panel data that cannot or have not been measured. Fixed effect models neutralize the bias of unobserved variables by considering only within-airline variation and ignoring variation in explanatory variables between airlines. These models essentially control for all time invariant unobserved variables by using each airline as its own control group. Unfortunately, fixed effect
model estimation issues can be reduced by employing linear regression models with error terms designed for the analysis of panel data. For this research, Parks’ method (SAS PROC TSCSREG) is the best compromise since it includes capabilities for estimating autocorrelation of variables over time in the quarterly measurements of independent variables, contemporaneous correlation of cross-sectional variables between airlines, and heteroscedasticity that might result from differing scales of airline operations (Parks 1967). In a Monte Carlo study of panel data estimators, Reed and Haichun (2011) conclude that Parks’ algorithm is the most efficient estimator when the ratio of number of time periods T to the number of cross sectional entities N is greater than 1.5. The ratio is 1.77 for this study. We also note that Parks’ method has previously been used for analysis of similar panel data (Tsikritsis & Heineke, 2004; Tsikritsis, 2007).

A fixed effects regression model using Parks’ algorithm for estimation can be expressed as the following linear regression model with dependent variable $Y_{it}$, where index $i = 1, 2, ... 9$ indexes the cross-sectional unit of analysis and $t = 1, 2, ... 16$ indexes the time period. The fixed effect dummy variables are represented by $\alpha_i$ the unknown intercept for each airline. The explanatory variables are represented by $X_{it}$, the parameter coefficients by $B_i$, and the model errors by $u_{it}$.

$$Y_{it} = \sum_{p=1}^{P} X_{it} B_i + \alpha_i + u_{it}$$

(2)

$P$ is the number of explanatory variables. Parks’ (1967) method is essentially a first-order autoregressive model with simultaneous contemporaneous correlation between cross-sections in which the random errors $u_{it}$, have the following non-spherical covariance structure.

- $E(u_{it}^2) = \sigma_{ii}$: heteroscedasticity, error variability is constant within an airline but varies between airlines
- $E(u_{it}u_{jt}) = \sigma_{ij}$: contemporaneous correlation between cross-sectional variables
- $u_{it} = \rho_i u_{it-1} + \varepsilon_{it}$: errors express a first order autoregressive time series

The Parks’ algorithm (Parks 1967) first estimates the matrix of model errors, $E(uu')$ by a two stage procedure. The model parameters are then estimated by generalized least squares, producing an estimator that is consistent and asymptotically normally distributed.

**DISCUSSION OF EXPERIMENTAL RESULTS**

The objective of this study is first, an empirical case study linking structural service delivery choices to service operations profitability, and secondly to provide insight into the effectiveness of specific structural design choices in the industry investigated. The SAS PROC TSCREG procedure including dummy variables to control for unobserved variables was used to estimate Parks’ time series cross-sectional regression model. All variables in the model have been standardized to facilitate comparison of parameter magnitudes. Mean levels of the raw (prior to standardization) dependent variable and the explanatory variables are given in Table 2 by airline. Estimates of model parameters are summarized in Table 3 with the service delivery structural choice variables ranked in decreasing magnitude.
Table 2: Descriptive statistics for model variables

<table>
<thead>
<tr>
<th>CARRIER</th>
<th>Mean Profitability</th>
<th>Mean Flight Conc.</th>
<th>Mean Scale</th>
<th>Mean Capacity Mgmt.</th>
<th>Mean Complexity</th>
<th>Mean Rivalry</th>
</tr>
</thead>
<tbody>
<tr>
<td>American</td>
<td>0.088</td>
<td>0.529</td>
<td>27560</td>
<td>0.798</td>
<td>6.250</td>
<td>1.679</td>
</tr>
<tr>
<td>Jet Blue</td>
<td>-3.853</td>
<td>0.556</td>
<td>6276</td>
<td>0.823</td>
<td>1.563</td>
<td>1.669</td>
</tr>
<tr>
<td>Continental</td>
<td>-0.818</td>
<td>0.578</td>
<td>12879</td>
<td>0.815</td>
<td>4.250</td>
<td>1.453</td>
</tr>
<tr>
<td>Delta</td>
<td>0.680</td>
<td>0.541</td>
<td>22272</td>
<td>0.781</td>
<td>5.938</td>
<td>1.856</td>
</tr>
<tr>
<td>AirTran</td>
<td>-4.437</td>
<td>0.534</td>
<td>4173</td>
<td>0.732</td>
<td>2.000</td>
<td>2.023</td>
</tr>
<tr>
<td>Northwest</td>
<td>-0.723</td>
<td>0.606</td>
<td>12667</td>
<td>0.805</td>
<td>6.563</td>
<td>1.346</td>
</tr>
<tr>
<td>United</td>
<td>-1.751</td>
<td>0.586</td>
<td>21277</td>
<td>0.810</td>
<td>7.000</td>
<td>1.846</td>
</tr>
<tr>
<td>US Air</td>
<td>-0.972</td>
<td>0.539</td>
<td>9619</td>
<td>0.771</td>
<td>7.813</td>
<td>1.534</td>
</tr>
<tr>
<td>Southwest</td>
<td>9.574</td>
<td>0.249</td>
<td>22166</td>
<td>0.714</td>
<td>1.000</td>
<td>1.265</td>
</tr>
<tr>
<td>All Airlines</td>
<td>-0.246</td>
<td>0.524</td>
<td>15432</td>
<td>0.783</td>
<td>4.708</td>
<td>1.630</td>
</tr>
</tbody>
</table>

Profit Impact of Service Delivery Structural Choices

The first objective of this research is to provide some insight into the importance of the structural choices on the service organizations profitability. We rely on the model R-Square (proportion of the variation in profitability explained by the model’s explanatory variables) to provide this insight. The model estimates provide strong support for the Service System Triad framework of service delivery articulated by Roth and Menor (2003). The service system structural design choices investigated in this research have a significant effect on a service organization’s operational profitability. The model’s coefficient of multiple determination (R-Square) value of 0.81 suggests a high proportion of the variation in profitability is explained by the model variables and the unobserved variation estimated by the fixed effect dummy variables. Excluding the dummy variables, the model’s explanatory variables account for approximately 0.65 of the variation in profitability. Almost two thirds of the industry’s differences in operational profitability are explained by the strategic choice decisions made by the nine airlines. T tests for the significance of model parameter estimates are also evidence of the importance of the structural choice variables. Table 3 reveals all structural choice variables are highly significant with the possible exception of operations scale with p = 0.163. We chose to leave this in the model and remind the reader that p values for fixed effect models are higher than ordinary least square regression estimates.

This case study is conducted in an industry whose basis for competition has been characterized by Porter (2008) as pure price competition. While these findings may not necessarily generalize to other service industries they do suggest the importance of structural design choices in industries including insurance, public services, and health care.
Table 3: Statistics and parameters of estimated model

<table>
<thead>
<tr>
<th>Estimation Method</th>
<th>Parks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Cross Sections</td>
<td>9</td>
</tr>
<tr>
<td>Time Series Length</td>
<td>16</td>
</tr>
</tbody>
</table>

Fit statistics

<table>
<thead>
<tr>
<th></th>
<th>SSE</th>
<th>DFE</th>
<th>MSE</th>
<th>Root MSE</th>
<th>RMSquare</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSE</td>
<td>25.49</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE</td>
<td>0.19</td>
<td></td>
<td>0.19</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td>R-Square</td>
<td>0.81</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standardized parameter estimates

| Structural Design Variable | Parameter Estimate | Error | t Value | Pr. > |t| |
|----------------------------|--------------------|-------|---------|--------|-----|
| Market Rivalry             | -1.236             | 0.185 | -6.69   | <.0001 |
| Fleet Complexity           | -0.848             | 0.132 | 6.44    | <.0001 |
| Operations Scale           | 0.232              | 0.165 | 1.40    | .1626  |
| Route Structure            | -0.224             | 0.076 | 2.93    | <.0001 |
| Capacity Mgmt.             | 0.068              | 0.029 | 2.33    | 0.0214 |

Service Delivery Structural Choice Priorities for the Industry

The standardized parameter estimates of Table 4 prioritize the potential of structural design choices for increasing operational profitability as follows: 1) focusing on flight segments served by fewer rivals; 2) reducing aircraft fleet complexity; 3) increasing operations scale; 4) reducing the centrality of the network flight structure; and 5) effective capacity management processes for increasing the load factor.

The model estimate of the impact of market rivalry confirms that price competition between rivals’ flight networks has a major negative impact on operational profitability, with a path estimate of -1.236 (p<0.0001). This evidence provides strong support for Hypothesis 4. Profitability is enhanced by designing flight networks that focus on city-pairs that are served by a minimum number of competitors or by multimarket competitors (rivals that serve similar market choices). This finding supports Porter’s (2008) conclusion that price competition as practiced by the domestic airline industry is the most destructive basis for competition; it transfers profits directly from the industry to customers.

The estimated effect of aircraft fleet complexity on service profitability is -0.848 (p<0.0001). This result confirms hypothesis 2 and establishes that the domestic airline industry may be investing in too many different aircraft models. The results suggest that service profitability can be increased by reducing the complexity of aircraft fleets. Recall the service structural design decision defining aircraft fleet complexity is a complex tradeoff of the benefits of matching capacity with demand and the increasing costs of more complex fleets. Each additional aircraft model creates a new cost driver including a set of unique maintenance procedures, additional inventories of new spare parts, repair items, and pilot training/certification. The benefits of
higher fleet complexity (more aircraft models) are an improved capability to match aircraft capacity and operating characteristics to route demand on individual flight segments. This can reduce the necessity of consolidating passengers at hubs and increase direct flights from origin to destination.

An increase in the scale of operations in the domestic airline industry are estimated to directly increases service operations profitability by 0.232 (p=0.0001), confirming Hypothesis 3. The interpretation of this result is that if all other variables are held constant, a unit increase in the scale of flight operations will increase operational profitability by 0.232. This is consistent with the most recent research of Johnston and Ozment who conclude “the largest major US airlines have enjoyed increasing returns to scale for the past 22 years.” Increasing scale can be accomplished by internal growth or through an airline merger with the latter being used in the recent past. Mergers enable airlines to rationalize the route structure; create new flight connections; combine support functions such as purchasing, maintenance, and repairs; and reduce competitive rivalry on some flight segments. The combined airlines can reduce the total number of hubs they jointly operate and increase the number of direct flights.

The estimate for the network routing structure is -0.224 (p=0.0001). This confirms Hypothesis 1 that less centralized flight networks increase operational profitability. Recall from section 3.1.1 the economic tradeoff in network design is the ability to aggregate passengers at hubs (increasing load factors) versus the lean advantages of routing passengers more directly from origin to destination. The sign of this parameter is interpreted to mean that, for this industry, profitability can be increased by deploying less centralized flight structures, focusing on more direct flights and de-emphasizing itineraries routed through network hubs.

In the airline industry capacity management is the structural choice of the number of aircraft seats to deploy to meet anticipated demand. It is also influenced by revenue management processes designed to maximize the load factor. For many years the industry expanded capacity faster than demand, leaving seats unfilled. The model estimate for capacity management is 0.068 (p=0.0214), which implies that structural design decisions to restrain capacity and increase load factors will increase profitability, confirming hypothesis 5. Capacity restraint has been identified by U. S. GAO (2014) as a major reason for the improvement in US airline earnings since 2007.

**CONCLUSIONS AND IMPLICATIONS**

There are several unique aspects of this research we would like to highlight for the reader. Our conceptual model measures the direct link between fundamental strategic design choices and operational profitability. By fundamental choices we mean decisions that can be implemented at the managerial level. Managerial choices include the selection of city pairs to serve considering the level of rivalry, the degree of centralization of the flight network, the resolution of the cost and benefit tradeoff of complex aircraft fleets, and the number of flights to schedule. This differs from prior research studies whose explanatory variables are productivity or utilization metrics. A manager is not able to choose a 90% load factor; the load factor is a performance metric achieved, in part, by effective design decisions. Our model estimates the impact of five service delivery structural design choices for nine industry competitors. It is also noteworthy that we use continuous variables to measure the managers’ fundamental design choices. For example, some prior studies use a binary variable and human judgment to categorize an airline’s flight
network as either a hub-and-spoke or point-to-point. A data-driven hub centralization metric is used in this research to provide richer information about the choice of this design variable. Table 2 reveals that Jet Blue, frequently categorized as focused on point-to-point flights, actually has a highly centralized flight network more closely resembling the legacy hub airlines. Finally, we recognize a relationship between lean consumption (Womack & Jones, 2005) and profitability. The customer’s perceived value of the total service concept can be gauged by our metric for network routing structure. Networks with more centralized routing structures create longer and less direct flights potentially lowering the customer perceived value. Unfortunately, the data does not allow us to decompose the aggregate effect of network structure into a customer value component and a cost economics component. The supply-side cost economics are a complex tradeoff of the benefits of passenger aggregation and the costs of longer flights, more flight segments, and the variability induced by network centralization.

The analysis provides strong empirical support for the architecture of the Service Delivery System (Roth & Menor, 2003). The conceptual model measures key elements of the service delivery structural choices. Approximately 65% of the differences in operational profitability are explained by the five structural design choices investigated in this research. We note that this estimate is for an industry characterized by intense price competition. This level of support may not generalize to other industries and particularly those where differentiation is the basis of competition.

Our research demonstrates the potential for large operational data sets to provide priorities for improvement. Analysis of over twelve million flights for nine domestic airlines over a four year time period reveal that operational profitability can be increased by: (1) avoiding competitive rivalry in city-pairs served; (2) deploying less complex aircraft fleets; (3) increasing the scale of operations; (4) decreasing reliance on hubs in the flight network; and (5) effective control of the capacity of aircraft deployed. It is interesting to note that since 2007 the industry has achieved priority 3, higher scale of operations through four mergers. Figure 3 depicts the magnitude of the impact of each service structural design choice impacts on profitability. The two most significant choices, market rivalry, and fleet complexity collectively represent 80% of impact on profitability while capacity management is 3%. A possible explanation is that capacity management has been extensively researched for decades. Its impact is well understood and industry competitors today may have achieved parity for capacity management. By parity, we mean the economics are understood and all organizations have similar priorities, skills, and capabilities. An example is the application of dynamic revenue management (Sen 2013) to adapt seat prices to a timeline of seat sales and the overbooking of seats to compensate for no-shows. Today these skills are well developed and it is feasible that all nine competitors have reasonably similar capabilities. By contrast there is less clarity in the research literature on the decisions for market rivalry, fleet complexity and centralization of the flight network. These decisions involve a complex set of economic tradeoffs that are not as intuitive as scale and capacity management.
While earlier studies on airline performance emphasized the significance of scale and capacity management, this research suggests the importance of some new themes, market rivalry and complexity. The impact of market rivalry is 48% of the total impact of the five strategic design choices investigated in this research. It has been evident that the domestic airlines have not been able to differentiate their service offerings and that price and convenience are the basis for customer purchase decisions. Porter (2008) observed that price competition, as practiced by the domestic airline industry, is the most destructive basis of competition. Airlines must become increasingly aware of number of competitors on encountered on each segment of their flight network and of the competitive behavior of these rivals. The complexity of the aircraft fleet is the second strategic theme highlighted by our findings. It represents 33% of the total impact. Fleet complexity varies from 1 for Southwest Airlines to 7.8 for U.S. Airlines. The arithmetic mean of fleet complexity for all airlines is 4.7. The results provide evidence that the aircraft fleets are to complex. Too many different configurations of aircraft are being used in domestic service. Some efforts by airlines with high fleet complexity to rationalize their aircraft choices is warranted.

The reader is cautioned that the findings of this research are limited by several constraints. First the data window used is intentionally limited to a relatively short four year interval. Extending the data window beyond 2007 will not improve model estimates. While the extension would provide a longer time series, the ensuing mergers between airlines would limit the number of organizations for analysis. Extending the time series earlier than 2004 exposes the economic estimates to the post 9/11/2001 shocks when flight operations were suspended and airlines required government subsidies. Another consideration is that longer data windows undermine the model’s ability to detect shifting strategic priorities. For example, Inzerilli and Jara-Diaz (1994) suggest that load factor is the single most important measure of operational performance. Our research from 2004-2007 suggests that load factor has been replaced by
market rivalry as the dominant strategic priority. Obviously, research data windows that cover decades of operational data are less sensitive detecting strategic shifts.

Limitations in estimating the empirical model are described in Section 3.4. These limitations include potential bias from unobserved variables and departures from the ordinary least square error assumptions. Some of the unobserved variation is from factors beyond the scope of this study, including differences in airlines' execution capabilities, differences in infrastructure, and differences in the integration methods employed by the airline (Roth and Menor, 2003). The bias caused by unobserved variables is minimized by the selection of a fixed effect regression model. Allison (2009) discusses complications that fixed effects models are not able to resolve. A primary concern is that fixed effect models only control for time-invariant unobserved variables. We feel relatively confident our experimental design minimizes the potential bias of time-varying unobserved variables. We highlight that the short four year time window is a stable economic period absent any significant external shocks. Finally any residual time effects can be absorbed in the autoregressive error becoming part of the regression noise. It is also noteworthy that an exploratory model was estimated with time period dummies. There was no evidence of significant time effects in the model. Estimation issues that include model errors exhibiting heteroscedasticity, contemporaneous correlation, and an autoregressive time series are alleviated by using Park’s (1967) method.

References


